Research on Logistics Vehicle Routing Optimization Based on Improved Ant Colony Algorithm

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Keywords: Logistics vehicle; Route optimization; Improved ant colony algorithm; 2-opt algorithm

Abstract: Aiming at the multi-objective optimization problem in logistics distribution, in order to manage vehicle routing more reasonably, a logistics distribution path planning model based on improved ant colony optimization algorithm is proposed to minimize the distribution cost. Firstly, the logistics distribution vehicle scheduling model is analyzed, and then on the basis of ant colony algorithm, 2-opt algorithm is used to improve it. When the search falls into local optimum, the probability of random selection is increased to avoid the premature phenomenon of ant colony. Finally, an example is given to validate the model. The results show that under the same environment, compared with the traditional ant colony algorithm, the improved algorithm can optimize the distribution path accurately, has faster optimization speed, and can effectively reduce the cost of logistics distribution.

1. Introduction

With the continuous development and progress of society, logistics distribution has become more and more important in the national economy. Vehicle routing optimization and vehicle scheduling problems in the process of logistics transportation have gradually been paid attention to. Vehicle routing problem of logistics distribution is to organize the demand points effectively, optimize the distribution path, and ensure that vehicles can complete the logistics distribution task with the shortest journey and the least time under the constraints of time and cargo demand [1-2]. Reasonable distribution routes can improve the efficiency of logistics distribution, reduce costs and improve the profits of enterprises. Therefore, vehicle routing optimization scheduling management has become a key issue in the field of logistics distribution.

As logistics distribution routing optimization is a multi-objective optimization problem, heuristic intelligent optimization algorithm is more suitable for solving this problem. At present, genetic algorithm, ant colony algorithm and particle swarm optimization are constantly applied in the field of path optimization, which greatly improves the search speed and global convergence, and can achieve better results. However, with the increase of search routes, these algorithms often appear "premature" phenomenon, which affects the speed and accuracy of optimization. Therefore, based on the ant colony algorithm, this paper uses 2-opt method to improve the ant colony algorithm. When the search falls into local optimum, it increases the probability of random selection, so as to avoid the phenomenon of "premature" ant colony.

2. Improved ant colony algorithms

2.1 Ant colony algorithm

Ant colony algorithm is a probabilistic algorithm to simulate ants' foraging behavior. In the process of foraging, it is difficult for a single ant to find the shortest path to food. When the ants gather, the probability of finding the shortest path will be greatly increased. Because the total amount of pheromone carried by a single ant is constant, the shorter the path length, the higher the concentration of pheromone released by the ant, and the ant will choose the path with higher pheromone concentration. This guidance mechanism has two functions: one is to guide ants to make path selection, that is, positive feedback. Secondly, ant colony algorithm is generated according to

  DOI: 10.25236/aisct.2019.091

the mechanism of continuously dispersing into the air so that ants can search continuously until they find the shortest path. The principle of ant colony algorithm is shown in Figure 1.

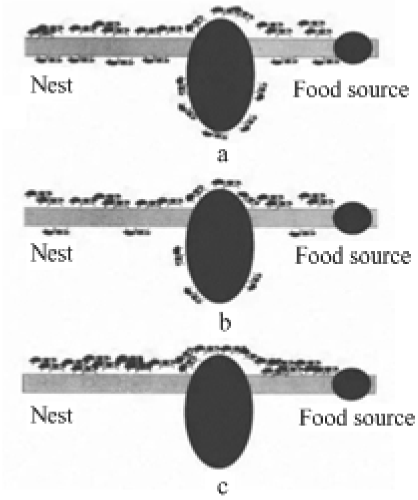

Fig.1 Principle of Ant Colony Algorithms

There are two paths from the nest to the food source. The probability of initial ant colony selection is the same. Because the above path is shorter, the initial ant colony will release higher pheromone concentration after walking, and the latter ant colony will probably choose this path. Over time, later ant colonies will choose this shorter path. Ant colony algorithm is widely used in vehicle routing optimization because of its strong robustness and fast solving speed.

The foraging behavior of ants is simulated, and the three-dimensional space problem is transformed into a two-dimensional model, which can be expressed as [3]:

$$m = \sum_{i=1}^{n} C_i(t) \tag{1}$$

In the process of ant routing, the choice of path usually depends on the concentration of pheromone and the amount of heuristic information. The probability of an ant choosing a path is as follows:

$$P_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)^{\alpha}[\eta_{ij}(t)]^{\beta}]}{\sum\limits_{s \in allowed_k} [\tau_{ij}(t)^{\alpha}[\eta_{ij}(t)]^{\beta}]} & j \in allowed_k \\ 0 & otherwise \end{cases} \tag{2}$$

Where: $P_{ij}(t)$ —Probability of ants from point *i* to point *j* at time t; $\tau_{ij}(t)$ —Pheromone left by ants on ij Road;

$\eta_{ij}(t)$ —Heuristic function; α —Information heuristic factor; β —Expectation heuristic factor.

Ants will leave a lot of pheromones when searching for the shorter paths, so that the pheromone accumulation of shorter paths is more. It is precisely because of this positive feedback that "premature" phenomenon is prone to occur in the search process of the shortest path. In order to avoid the ant convergence to the sub-optimal solution too early on the shortest path, it is necessary to update the pheromone left by the ant that finds the best path after each cycle. The rules of pheromone updating are as follows:

$$\tau_{ij}(t+n)=(1-\rho)*\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{3}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{4}$$

Where: ρ —Volatilization of pheromones; $\Delta\tau_{ij}^{k}(t)$ —Increment of pheromone.

The pheromone is updated by global updating method. The formula is as follows:

$$\Delta\tau_{ij}(t)^{k}=\begin{cases}\dfrac{Q}{L_{ij}} & \text{Ants Pass ij Section}\\ 0 & \text{otherwise}\end{cases} \tag{5}$$

After the ant population path finding is completed, a set of paths are formed, the iteration ends, and pheromone updates are carried out. The pheromone update value is the sum of the paths each ant travels in the ant colony. For an ant, if he travels a certain distance, the pheromone increment generated by the ant on this path is the total amount of pheromone generated by the ant divided by the length of the path. Where he does not pass, the pheromone increment caused by the ant is 0.

2.2 Improvement of Ant Colony Algorithms

Ant colony algorithm is a probabilistic algorithm used to optimize the path. It belongs to the heuristic global algorithm, which seeks the optimal solution through the cooperation between individuals. In this algorithm, ants select the next node by judging pheromone concentration. However, when searching to a certain extent, the pheromone of the path is constantly increasing, which is prone to prematurity and stagnation, and cannot achieve global optimization. Therefore, this paper uses 2-opt method to improve the ant colony algorithm. When the search falls into local optimum, the probability of random selection is increased, so as to avoid the premature phenomenon of ant colony [4].

2-opt algorithm is based on the heuristic idea of "exchange", which converts one path to another. In a given feasible path, as long as the value of the objective function can be reduced, the algorithm will operate repeatedly in the selected set until the local optimal path is generated. Its principle is as follows: Replacing $(i,i+1),(j,j+1)$ with $(i,j),(i+1,j+1)$, path $(i+1,\cdots,j)$ is reversed after transformation, and the weight of path decreases after exchange, which satisfies the following conditions:

$$C_{i,j}+C_{i+1,j+1}<C_{i,i+1}+C_{j,j+1} \tag{6}$$

The structure of the 2-opt algorithm model is shown in Figure 2.

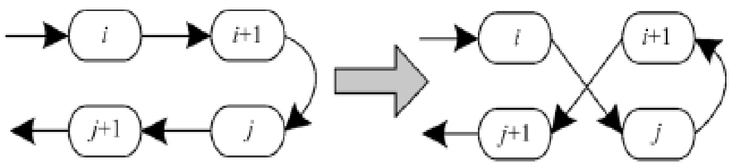

Fig.2 Principle of 2-opt algorithm

The steps of improving ant colony algorithm are as follows:

The ant colony algorithm is improved, assuming that M ants are placed at the distribution customer point. At the beginning of the search, each ant randomly chooses a distribution customer point and finds the optimal solution in each iteration process. When the iteration is completed, the optimal solution obtained by the iteration is formed into an optimal solution pool. In the optimal solution pool, the 2-opt method is used to optimize the solution pool and the global optimal solution is obtained. The flow chart of the algorithm is shown in Figure 3.

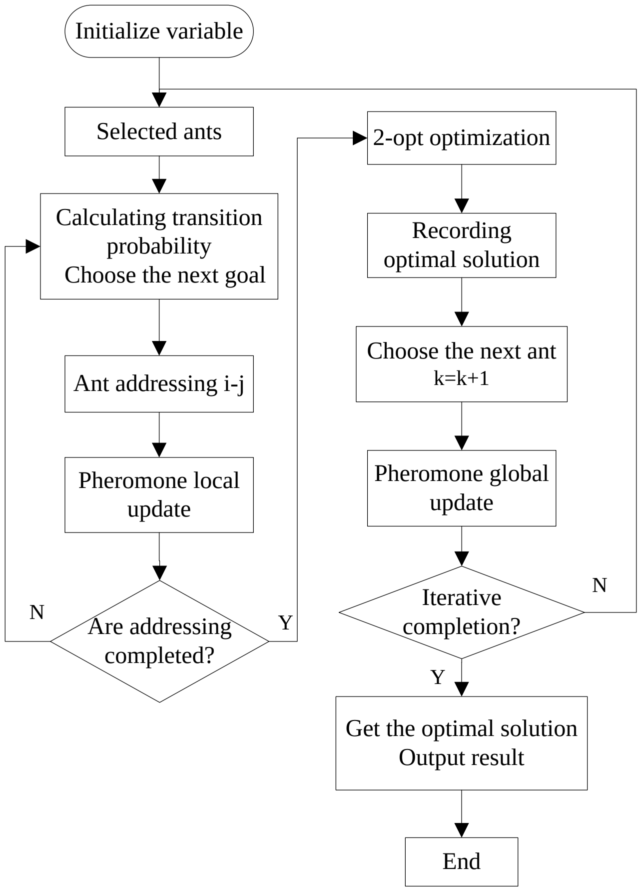

Fig.3 Improving the Flow of Ant Colony Algorithms

3. Case verifications

It is known that a logistics company has eight distribution vehicles, the maximum load of each vehicle is 5 t, and the maximum distance of each vehicle is 100 km. It needs to provide services to 20 customers at the same time. The location of customers is shown in Table 1.

Tab.1 Customer position coordinates

Customer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
X	13	19	15	4	15	4	11	9	13	14	7	15	2	17	7	1	12	13	6	10
Y	8	15	11	11	12	11	8	8	2	5	17	3	9	11	1	3	20	15	6	15

The ant colony algorithm and the improved ant colony algorithm are used to solve the problem iteratively.

The values of the parameters are: $\alpha = 2$, $\beta = 3$, $\rho = 0.75$, The adaptive parameters are: $\zeta = 0.5$,The total amount of pheromones is: $Q = 100$, The maximum number of iterations is: $N = 200$, Number of ants 60,Running 10 times. The iteration process is shown in Figure 4.

In the graph, the improved ant colony algorithm obtains the optimal solution after 58 iterations, while the ant colony algorithm obtains a sub-optimal solution after 130 iterations. The convergence speed is greatly improved, and the addressing accuracy is optimized by about 8%.

The minimum distribution distance and maximum distribution distance are taken as research indicators for analysis, and compared with the traditional ant colony algorithm. The results are shown in Table 2.

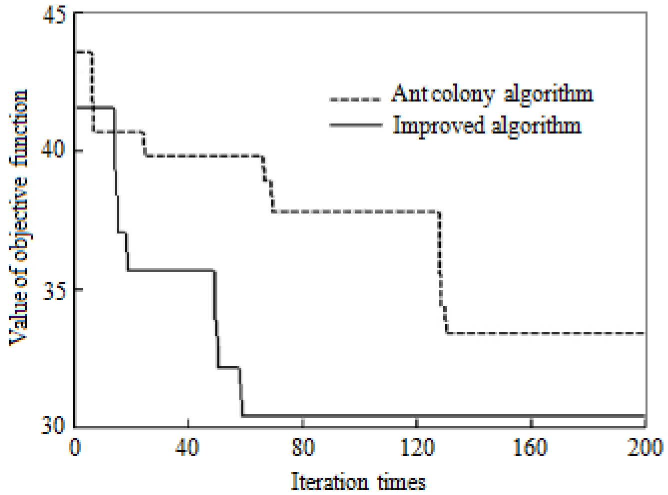

Fig. 4 Iterative process graph

Tab.2 Comparisons of Algorithmic Results

Algorithm	Ant colony algorithm	Improved algorithm	Optimization range
Minimum Distribution Distance(km)	110	96	12.7%
Maximum Distribution Distance(km)	115	102	11.3%

The results show that the improved distribution distance reduces effectively, the minimum distribution distance is optimized by 12.7%, and the maximum distribution distance is optimized by 11.3%, which improves the distribution efficiency and enterprise operation cost.

4. Conclusions

Aiming at the shortcomings of heuristic algorithm in logistics distribution path optimization, this paper uses 2-opt algorithm to improve the ant colony algorithm, and proposes a logistics distribution path planning model based on Improved Ant Colony Optimization algorithm. The results show that compared with the traditional ant colony algorithm, the improved algorithm can accurately optimize the logistics distribution path, has a faster optimization speed, can effectively reduce the cost of logistics distribution, and has a certain reference value for the research of logistics distribution path optimization.

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